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Ref #	Hits	Search Query	DBs	Default Operator	Plurals	Time Stamp
L1	100	("20050246297" "20050209982" "5502688" "6135965" "6445988" "5581657" "5486996" "6360191" "5214746" "5249259" "5706321" "5778317" "5809488" "5832466" "5867397" "6023459" "6470261" "6553357" "6601053" "6658396" "20020059154" "20020077756" "20020174079" "20030191728" "20030204319" "20030204320" "20030212645" "20040030503" "20040177081" "20050004905" "20050055340" "20060025961" "5777888" "6751601" "6944319" "7016885" "20020032557" "20040093315" "20050147291" "20050147292" "5862513" "5251286" "5373486" "5444619" "5828981" "5940777" "20040133531" "5245696" "5568590" "5701400").pn.	US-PGPUB; USPAT; EPO; JPO; DERWENT; IBM_TDB	OR	OFF	2006/09/22 22:20
L2	797582	(neural neuron neuronic neuronal) adj (net network) (artificial adj intelligence) ai learning logic inference neuralnet ((computer machine) adj learning)	US-PGPUB; USPAT; EPO; JPO; DERWENT; IBM_TDB	OR	OFF	2006/09/22 22:22
L3	164298	(genetic adj1 algorithm) GA	US-PGPUB; USPAT; EPO; JPO; DERWENT; IBM_TDB	OR	OFF	2006/09/22 22:23
L4	393	(neural adj1 (net network) adj1 (ensemble set group))	US-PGPUB; USPAT; EPO; JPO; DERWENT; IBM_TDB	OR	OFF	2006/09/22 22:24
L5	1938	negative adj1 correlation	US-PGPUB; USPAT; EPO; JPO; DERWENT; IBM_TDB	OR	OFF	2006/09/22 22:25
L6	10	((open adj1 hole) (case adj1 hole)) near2 (logging adj1 data)	US-PGPUB; USPAT; EPO; JPO; DERWENT; IBM_TDB	OR	OFF	2006/09/22 22:26

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L7	11	((open adj1 hole) (case adj1 hole)) same (logging adj1 data)	US-PGPUB; USPAT; EPO; JPO; DERWENT; IBM_TDB	OR	OFF	2006/09/22 22:26
L8	0	pulse adj1 neutron adj1 data	US-PGPUB; USPAT; EPO; JPO; DERWENT; IBM_TDB	OR	OFF	2006/09/22 22:27
L9	663	pulse near2 neutron	US-PGPUB; USPAT; EPO; JPO; DERWENT; IBM_TDB	OR	OFF	2006/09/22 22:27
L10	17260	2 and 3	US-PGPUB; USPAT; EPO; JPO; DERWENT; IBM_TDB	OR	OFF	2006/09/22 22:27
L11	88	10 and 5	US-PGPUB; USPAT; EPO; JPO; DERWENT; IBM_TDB	OR	OFF	2006/09/22 22:33
L12	1	11 and 6	US-PGPUB; USPAT; EPO; JPO; DERWENT; IBM_TDB	OR	OFF	2006/09/22 22:29
L13	4	3 and 4 and 5	US-PGPUB; USPAT; EPO; JPO; DERWENT; IBM_TDB	OR	OFF	2006/09/22 22:30
L14	9	4 and 5	US-PGPUB; USPAT; EPO; JPO; DERWENT; IBM_TDB	OR	OFF	2006/09/22 22:47
L15	8204	well near2 (log record)	US-PGPUB; USPAT; EPO; JPO; DERWENT; IBM_TDB	OR	OFF	2006/09/22 22:33
L16	3492607	oil gas	US-PGPUB; USPAT; EPO; JPO; DERWENT; IBM_TDB	OR	OFF	2006/09/22 22:33

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L17	337	15 with 16	US-PGPUB; USPAT; EPO; JPO; DERWENT; IBM_TDB	OR	OFF	2006/09/22 22:34
L18	50	2 and 17	US-PGPUB; USPAT; EPO; JPO; DERWENT; IBM_TDB	OR	OFF	2006/09/22 22:34
L19	0	14 and 18	US-PGPUB; USPAT; EPO; JPO; DERWENT; IBM_TDB	OR	OFF	2006/09/22 22:48
L20	23	3 and 4	US-PGPUB; USPAT; EPO; JPO; DERWENT; IBM_TDB	OR	OFF	2006/09/22 22:48
L21	0	20 and 18	US-PGPUB; USPAT; EPO; JPO; DERWENT; IBM_TDB	OR	OFF	2006/09/22 22:48

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Relevance scale **1** Intrusion and privacy: Exploiting unlabeled data in ensemble methods 

 Kristin P. Bennett, Ayhan Demiriz, Richard Maclin
 July 2002 **Proceedings of the eighth ACM SIGKDD international conference on Knowledge discovery and data mining**

Publisher: ACM Press

Full text available:  pdf(719.46 KB) Additional Information: [full citation](#), [abstract](#), [references](#), [index terms](#)

An adaptive semi-supervised ensemble method, ASSEMBLE, is proposed that constructs classification ensembles based on both labeled and unlabeled data. ASSEMBLE alternates between assigning "pseudo-classes" to the unlabeled data using the existing ensemble and constructing the next base classifier using both the labeled and pseudolabeled data. Mathematically, this intuitive algorithm corresponds to maximizing the classification margin in hypothesis space as measured on both the labeled and unlabeled ...

Keywords: boosting, classification, ensemble learning, semi-supervised learning

2 The principled design of large-scale recursive neural network architectures--dag-rnns and the protein structure prediction problem 

Pierre Baldi, Gianluca Pollastri
 December 2003 **The Journal of Machine Learning Research**, Volume 4

Publisher: MIT Press

Full text available:  pdf(231.40 KB) Additional Information: [full citation](#), [abstract](#), [references](#), [index terms](#)

We describe a general methodology for the design of large-scale recursive neural network architectures (DAG-RNNs) which comprises three fundamental steps: (1) representation of a given domain using suitable directed acyclic graphs (DAGs) to connect visible and hidden node variables; (2) parameterization of the relationship between each variable and its parent variables by feedforward neural networks; and (3) application of weight-sharing within appropriate subsets of DAG connections to capture ...

3 Genetic algorithms: Evolving neural network ensembles for control problems 

 David Pardoe, Michael Ryoo, Risto Miikkulainen
 June 2005 **Proceedings of the 2005 conference on Genetic and evolutionary computation GECCO '05**

Publisher: ACM Press

Full text available:  pdf(121.49 KB) Additional Information: [full citation](#), [abstract](#), [references](#), [index terms](#)

In neuroevolution, a genetic algorithm is used to evolve a neural network to perform a particular task. The standard approach is to evolve a population over a number of generations, and then select the final generation's champion as the end result. However, it is possible that there is valuable information present in the population that is not captured by the champion. The standard approach ignores all such information. One possible solution to this problem is to combine multiple individuals fro ...

Keywords: ensembles, genetic algorithms, neural networks, reinforcement learning

4 [Application of neural networks to biological data mining: a case study in protein sequence classification](#)

 Jason T. L. Wang, Qicheng Ma, Dennis Shasha, Cathy H. Wu
August 2000 **Proceedings of the sixth ACM SIGKDD international conference on Knowledge discovery and data mining**

Publisher: ACM Press

Full text available:  [pdf\(181.04 KB\)](#) Additional Information: [full citation](#), [references](#), [citations](#), [index terms](#)

Keywords: bioinformatics, biological data mining, feature extraction from protein data, machine learning, neural networks, sequence alignment

5 [Designing committees of models through deliberate weighting of data points](#)

Stefan W. Christensen, Ian Sinclair, Philippa A. S. Reed
December 2003 **The Journal of Machine Learning Research**, Volume 4

Publisher: MIT Press

Full text available:  [pdf\(205.46 KB\)](#) Additional Information: [full citation](#), [abstract](#), [references](#), [index terms](#)

In the adaptive derivation of mathematical models from data, each data point should contribute with a weight reflecting the amount of confidence one has in it. When no additional information for data confidence is available, all the data points should be considered equal, and are also generally given the same weight. In the formation of committees of models, however, this is often not the case and the data points may exercise unequal, even random, influence over the committee formation. In this ...

6 [Contributed articles on online, interactive, and anytime data mining: MobiMine: monitoring the stock market from a PDA](#)

 Hilol Kargupta, Byung-Hoon Park, Sweta Pittie, Lei Liu, Deepali Kushraj, Kakali Sarkar
January 2002 **ACM SIGKDD Explorations Newsletter**, Volume 3 Issue 2

Publisher: ACM Press

Full text available:  [pdf\(1.16 MB\)](#) Additional Information: [full citation](#), [abstract](#), [references](#), [citations](#)

This paper describes an experimental mobile data mining system that allows intelligent monitoring of time-critical financial data from a hand-held PDA. It presents the overall system architecture and the philosophy behind the design. It explores one particular aspect of the system---automated construction of personalized focus area that calls for user's attention. This module works using data mining techniques. The paper describes the data mining component of the system that employs a novel Four ...

7 [Cluster ensembles --- a knowledge reuse framework for combining multiple partitions](#)

Alexander Strehl, Joydeep Ghosh
March 2003 **The Journal of Machine Learning Research**, Volume 3

Publisher: MIT Press

Additional Information:

Full text available:  pdf(842.50 KB)[full citation](#), [abstract](#), [references](#), [citations](#), [index terms](#)

This paper introduces the problem of combining multiple partitionings of a set of objects into a single consolidated clustering *without* accessing the features or algorithms that determined these partitionings. We first identify several application scenarios for the resultant 'knowledge reuse' framework that we call *cluster ensembles*. The cluster ensemble problem is then formalized as a combinatorial optimization problem in terms of shared mutual information. In addition to a direct ...

Keywords: cluster analysis, clustering, consensus functions, ensemble, knowledge reuse, multi-learner systems, mutual information, partitioning, unsupervised learning

8 [Learning Ensembles from Bites: A Scalable and Accurate Approach](#) 

Nitesh V. Chawla, Lawrence O. Hall, Kevin W. Bowyer, W. Philip Kegelmeyer
December 2004 **The Journal of Machine Learning Research**, Volume 5

Publisher: MIT Press

Full text available:  pdf(3.34 MB) Additional Information: [full citation](#), [abstract](#), [references](#), [index terms](#)

Bagging and boosting are two popular ensemble methods that typically achieve better accuracy than a single classifier. These techniques have limitations on massive data sets, because the size of the data set can be a bottleneck. Voting many classifiers built on small subsets of data ("pasting small votes") is a promising approach for learning from massive data sets, one that can utilize the power of boosting and bagging. We propose a framework for building hundreds or thousands of such classifie ...

9 [Neural networks and dynamic complex systems](#) 

Geoffrey Fox, Wojtek Furmanski, Alex Ho, Jeff Koller, Peter Simic, Isaac Wong
March 1989 **Proceedings of the 22nd annual symposium on Simulation ANSS '89**

Publisher: IEEE Computer Society Press

Full text available:  pdf(1.44 MB) Additional Information: [full citation](#), [abstract](#), [references](#), [index terms](#)

We describe the use of neural networks for optimization and inference associated with a variety of complex systems. We show how a string formalism can be used for parallel computer decomposition, message routing and sequential optimizing compilers. We extend these ideas to a general treatment of spatial assessment and distributed artificial intelligence.

10 [Information access and retrieval \(IAR\): Text classification based on data partitioning](#) 

 [and parameter varying ensembles](#)

Yan-Shi Dong, Ke-Song Han

March 2005 **Proceedings of the 2005 ACM symposium on Applied computing SAC '05**

Publisher: ACM Press

Full text available:  pdf(231.21 KB) Additional Information: [full citation](#), [abstract](#), [references](#), [index terms](#)

Support vector machines (SVM) are among the best text classifiers so far. Meantimes, ensembles of classifiers are proven to be effective on many domains. It is expected that ensembles of SVM classifiers could achieve better performance. In this paper two types of ensembles on SVM classifiers, the data partitioning ensembles and heterogeneous ensembles, have been proposed and experimentally evaluated on three well-accepted collections. Major conclusions are that disjunct partitioning ensembles wi ...

Keywords: ensemble, support vector machines, text classification

11 [Article abstracts with full text online: Evaluation of various training algorithms in a](#)

11 neural network model for software engineering applications

 K. K. Aggarwal, Yogesh Singh, Pravin Chandra, Manimala Puri
July 2005 **ACM SIGSOFT Software Engineering Notes**, Volume 30 Issue 4

Publisher: ACM Press

Full text available:  [pdf\(412.13 KB\)](#) Additional Information: [full citation](#), [abstract](#), [references](#), [index terms](#)

Software Engineering as a discipline emerged in response to the software crisis perceived by the industry. It is a well known fact that at the beginning of any project, the software industry needs to know how much will it cost to develop and what would be the time required. Resource estimation in software engineering is more challenging than resource estimation in any other industry. A number of resource estimation methods are currently available and the neural network model is one of them. This ...

Keywords: neural network, resource estimation, software engineering, training algorithm

12 Research track posters: Model compression

 Cristian Buciluă, Rich Caruana, Alexandru Niculescu-Mizil
August 2006 **Proceedings of the 12th ACM SIGKDD international conference on Knowledge discovery and data mining KDD '06**

Publisher: ACM Press

Full text available:  [pdf\(1.09 MB\)](#) Additional Information: [full citation](#), [abstract](#), [references](#), [index terms](#)

Often the best performing supervised learning models are ensembles of hundreds or thousands of base-level classifiers. Unfortunately, the space required to store this many classifiers, and the time required to execute them at run-time, prohibits their use in applications where test sets are large (e.g. Google), where storage space is at a premium (e.g. PDAs), and where computational power is limited (e.g. hearing aids). We present a method for "compressing" large, complex ensembles into smaller ...

Keywords: model compression, supervised learning

13 Round robin classification

Johannes Fürnkranz
March 2002 **The Journal of Machine Learning Research**, Volume 2

Publisher: MIT Press

Full text available:  [pdf\(250.25 KB\)](#) Additional Information: [full citation](#), [abstract](#), [references](#), [citations](#), [index terms](#)

In this paper, we discuss round robin classification (aka pairwise classification), a technique for handling multi-class problems with binary classifiers by learning one classifier for each pair of classes. We present an empirical evaluation of the method, implemented as a wrapper around the Ripper rule learning algorithm, on 20 multi-class datasets from the UCI database repository. Our results show that the technique is very likely to improve Ripper's classification accuracy without having a hi ...

Keywords: class binarization, ensemble techniques, inductive rule learning, multi-class problems, pairwise classification

14 Technical Correspondence: A neural net compiler system for hierarchical

 **organization**

Rajeev Kumar
February 2001 **ACM SIGPLAN Notices**, Volume 36 Issue 2

Publisher: ACM Press

Full text available:  pdf(954.76 KB) Additional Information: [full citation](#), [abstract](#), [references](#)

We present a language framework for handling arbitrarily complex neural computations. The software architecture - which we call an **Artificial Neural Network Compiler for Hierarchical ORganization (ANCHOR)** - facilitates network hierarchy and simpler sub-mappings. We define a **Net Definition Language (NDL)** which is implemented in object-oriented programming paradigm; a trained network is decompiled bac ...

Keywords: compiler-decompiler, hierarchical networks, neural net definitions, neural programming language, superneuron

15 Research track: Mining concept-drifting data streams using ensemble classifiers 

 Haixun Wang, Wei Fan, Philip S. Yu, Jiawei Han
August 2003 **Proceedings of the ninth ACM SIGKDD international conference on Knowledge discovery and data mining**

Publisher: ACM Press

Full text available:  pdf(234.13 KB) Additional Information: [full citation](#), [abstract](#), [references](#), [citations](#), [index terms](#)

Recently, mining data streams with concept drifts for actionable insights has become an important and challenging task for a wide range of applications including credit card fraud protection, target marketing, network intrusion detection, etc. Conventional knowledge discovery tools are facing two challenges, the overwhelming volume of the streaming data, and the concept drifts. In this paper, we propose a general framework for mining concept-drifting data streams using weighted ensemble classifi ...

Keywords: classifier, classifier ensemble, concept drift, data streams

16 Special issue on learning from imbalanced datasets: Minority report in fraud 

 Clifton Phua, Damminda Alahakoon, Vincent Lee
June 2004 **ACM SIGKDD Explorations Newsletter**, Volume 6 Issue 1

Publisher: ACM Press

Full text available:  pdf(262.38 KB) Additional Information: [full citation](#), [abstract](#), [references](#), [citations](#)

This paper proposes an innovative fraud detection method, built upon existing fraud detection research and *Minority Report*, to deal with the data mining problem of skewed data distributions. This method uses backpropagation (BP), together with naive Bayesian (NB) and C4.5 algorithms, on data partitions derived from minority oversampling with replacement. Its originality lies in the use of a single meta-classifier (stacking) to choose the best base classifiers, and then combine these base ...

Keywords: fraud detection, meta-learning, multiple classifier systems

17 Building predictors from vertically distributed data 

Sabine McConnell, David B. Skillicorn
October 2004 **Proceedings of the 2004 conference of the Centre for Advanced Studies on Collaborative research**

Publisher: IBM Press

Full text available:  pdf(184.78 KB) Additional Information: [full citation](#), [abstract](#), [references](#), [index terms](#)

Due in part to the large volume of data available today, but more importantly to privacy concerns, data are often distributed across institutional, geographical and organizational

boundaries rather than being stored in a centralized location. Data can be distributed by separating objects or attributes: in the homogeneous case, sites contain subsets of objects with all attributes, while in the heterogeneous case sites contain subsets of attributes for all objects. Ensemble approaches combine t ...

18 Hypercube algorithms for neural network simulation: the *Crystal_Accumulator* and

 the *Crystal Router*

G. C. Fox, W. Furtmanski

January 1988 **Proceedings of the third conference on Hypercube concurrent computers and applications: Architecture, software, computer systems, and general issues - Volume 1**

Publisher: ACM Press

Full text available:  pdf(466.00 KB) Additional Information: [full citation](#), [abstract](#), [references](#), [citations](#), [index terms](#)

We discuss communication algorithms relevant for neural network modeling on distributed memory concurrent computers with a hypercube topology. Full, intermediate (medium range) and sparse network connectivities are analyzed. We point out that the flexible hypercube topology allows for the efficient implementation of the broad class of network algorithms with variety of connectivity patterns. We find algorithms index, crystal_router, fold an ...

19 The distributed boosting algorithm

 Aleksandar Lazarevic, Zoran Obradovic

August 2001 **Proceedings of the seventh ACM SIGKDD international conference on Knowledge discovery and data mining**

Publisher: ACM Press

Full text available:  pdf(625.23 KB) Additional Information: [full citation](#), [abstract](#), [references](#), [index terms](#)

In this paper, we propose a general framework for distributed boosting intended for efficient integrating specialized classifiers learned over very large and distributed homogeneous databases that cannot be merged at a single location. Our distributed boosting algorithm can also be used as a parallel classification technique, where a massive database that cannot fit into main computer memory is partitioned into disjoint subsets for a more efficient analysis. In the proposed method, at each boost ...

Keywords: Boosting, classifier ensembles, distributed learning

20 Attribute Clustering for Grouping, Selection, and Classification of Gene Expression Data

Wai-Ho Au, Keith C. C. Chan, Andrew K. C. Wong, Yang Wang

April 2005 **IEEE/ACM Transactions on Computational Biology and Bioinformatics (TCBB)**, Volume 2 Issue 2

Publisher: IEEE Computer Society Press

Full text available:  pdf(2.58 MB) Additional Information: [full citation](#), [abstract](#), [references](#), [index terms](#)

This paper presents an attribute clustering method which is able to group genes based on their interdependence so as to mine meaningful patterns from the gene expression data. It can be used for gene grouping, selection, and classification. The partitioning of a relational table into attribute subgroups allows a small number of attributes within or across the groups to be selected for analysis. By clustering attributes, the search dimension of a data mining algorithm is reduced. The reduction of ...

Keywords: Data mining, attribute clustering, gene selection, gene expression classification, microarray analysis.

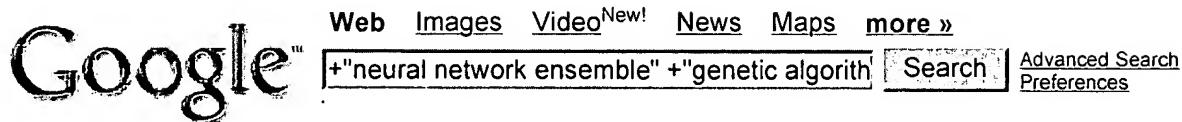
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Genetic Algorithm based Selective Neural Network Ensemble. Zhi-Hua Zhou Jian-Xin

Wu Yuan Jiang Shi-Fu Chen. National Laboratory for Novel Software ...

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[Genetic algorithm based selective neural network ensemble - group of 2 »](#)

ZH Zhou, JX Wu, Y Jiang, SF Chen - Proc. IJCAI - citeseer.ist.psu.edu

... and SF Chen", title = **"Genetic algorithm based selective neural network ensemble"** booktitle = "Proceedings ... learning via **negative correlation** - Liu, Yao ...

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[A constructive algorithm for training cooperative neural network ensembles - group of 5 »](#)

MM Islam, X Yao, K Murase - Neural Networks, IEEE Transactions on, 2003 - ieeexplore.ieee.org

... training is a special case of **negative correlation** learning ... in CNNE are trained by **negative cor-** relation ... the BKS method [25], **genetic-algorithm-based selective** ...

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[Using diversity in preparing ensembles of classifiers based on different feature subsets to minimize ... - group of 7 »](#)

G Zenobi, P Cunningham - Lecture Notes in Computer Science, 2001 - Springer

... were obtained by Liu (1999), who introduced a **negative correlation** penalty term to ... to find a diverse ensemble of neural networks using a **genetic algorithm**. ...

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[Neural network regularization and ensembling using multi-objective evolutionary algorithms - group of 5 »](#)

Y Jin, T Okabe, B Sendhoff - Evolutionary Computation, 2004. CEC2004. Congress on, 2004 - ieeexplore.ieee.org

... of two multi-objective optimization algorithms, the dynamic weighted aggregation (DWA) method and the elitist non-dominated sort- ing **genetic algorithm** (NSGA-II ...

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G Brown, JL Wyatt - 20th International Conference on Machine Learning (ICML'03 ... , 2003 - hpl.hp.com

... in **Neural Network Ensemble** Learning Methods ... Abstract We analyze the formal grounding

behind **Negative Correlation** (NC) Learning, an en- semble learning ...

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[Ensembling neural networks: Many could be better than all - group of 13 »](#)

ZH Zhou, J Wu, W Tang - Artificial Intelligence, 2002 - cs.nju.edu.cn

... In general, a **neural network ensemble** is constructed in ... an approach named GASEN (**Genetic Algorithm** based Selective ... Now we define the **correlation** between the i ...

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JX Wu, ZH Zhou, ZQ Chen - Proceedings of the 8th International Conference on Neural ... , 2001 - wujx.myrice.com

... investigate why and how **neural network ensemble** works ... neural net- works with

negative

correlation learning and ... pendently and then employs **genetic algorithm** to se ...
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Reducing fitness evaluations using clustering techniques and neural network ensembles - group of 3 »

Y Jin, B Sendhoff - Genetic and Evolutionary Computation Conference - Springer ... 13], decorrelation [16] or **negative correlation** [11,12 ... In this work, a **genetic algorithm** with local ... been used to generate the **neural network ensemble**, which can ...
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Forecasting time series with genetic fuzzy predictor ensemble

D Kim, C Kim - Fuzzy Systems, IEEE Transactions on, 1997 - [ieeexplore.ieee.org](#)
... Moreover, many hybrid systems of neural networks, **genetic algorithm**, and fuzzy logic have been also introduced for improving the performances of prediction [8 ...
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Combining Regression Estimators: GA-Based Selective Neural Network Ensemble - group of 4 »

ZH Zhou, JX Wu, W Tang, ZQ Chen - International Journal of Computational Intelligence and ..., 2001 - [cs.nju.edu.cn](#)
... In general, a **neural network ensemble** is constructed in two ... and Shavlik exploit a **genetic algorithm** to train ... Liu and Yao use **negative correlation** learning to ...
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M Pennington

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AJ Cannon, IG McKendry - International Journal of Climatology, 1999 - doi.wiley.com

... For each of the 15 predictor sets, **five neural networks** were initialized ... **Neural network ensemble** members were initialized with randomly assigned weight and ...

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[Explaining Predictions from a Neural Network Ensemble One at a Time - group of 7 »](#)

R Wall, P Cunningham, P Walsh - Proceedings of the 6th European Conference on Principles of ..., 2002 - Springer

... Explaining Predictions from a **Neural Network Ensemble** One at a Time ... calculated using

10 fold cross validation with an ensemble of **five neural networks** per fold ...

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[Neural Network Ensemble Based Ant Colony Classification Rule Mining](#)

C Chen, Y Chen, J He - log - doi.ieeecomputersociety.org

... In our experiment, every component neural network use three-layer BP network, and the **neural network ensemble** consists of **five neural networks** as the NEC4.5 ...

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[C4. 5 Rule Preceded by an Artificial Neural Network Ensemble for Medical Diagnosis](#)

M Pennington, A Sharkey, M Pennington - dcs.shef.ac.uk

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By Matt Pennington Dr Amanda Sharkey COM3021 8 th draft 07/05/2003 01:40 ...

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K Schmidt - 2003 - iis-web.coloradotech.edu

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